Image Dataset Curation
Workshop IV

Antonio Rueda-Toicen
AI Engineer

KI Service Zentrum, Hasso Plattner Institute
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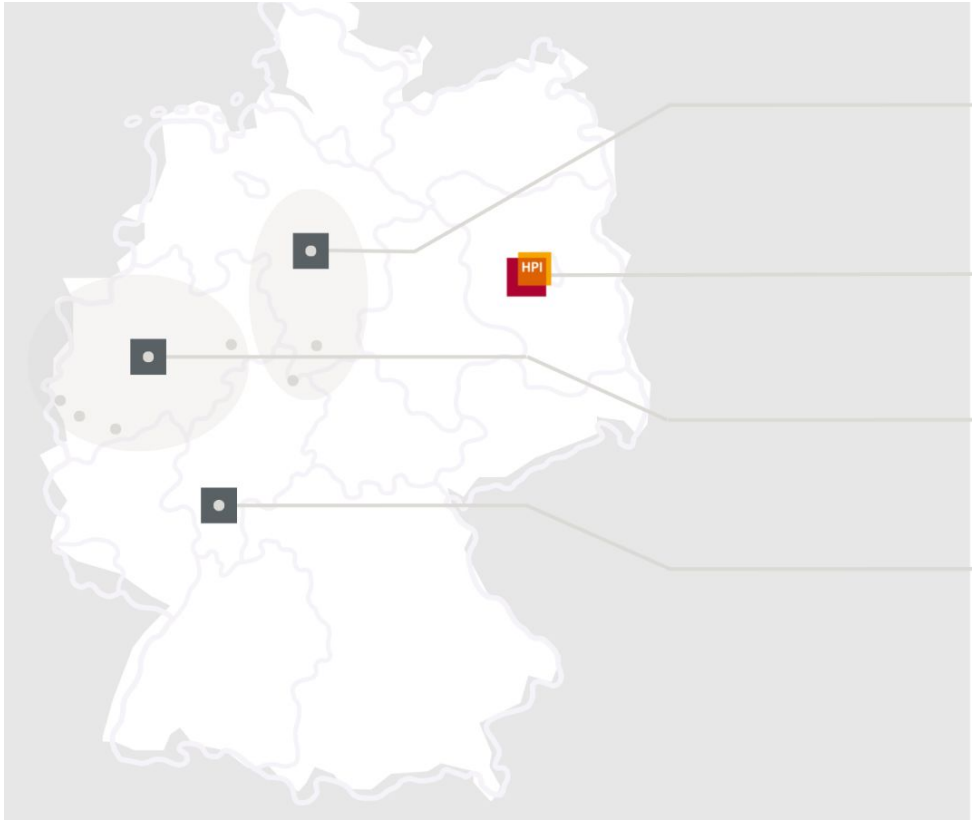
https://hpi.de/kisz/home.html



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Agenda

- Brief intro and learning objectives
- Overview of parts I and II of this workshop series
  - Understanding image embeddings
  - Scraping images from Google Images
- Classifying images with pretrained Resnets
- Multi-label vs single label classification
- Fine-tuning a Resnet with FastAI
- Review questions and discussion

What we expect you to have

- Some Python knowledge
- Curiosity :)

Learning objectives

At the end of the first workshop you will be able to:

- Describe use cases for image similarity in dataset curation
- Scrape images from Google Images or Bing
- Generate embeddings for images using a pretrained neural network
- Compare image pairs using cosine similarity
- Visualize embeddings in 3D using Tensorboard

Learning objectives

At the end of the second workshop you will be able to:

- Visualize image neighborhoods with k-nn
- Cluster images using k-medoids
- Select representative images

Learning objectives

At the end of the third workshop you will be able to:

- Classify images with a pre-trained Resnet
- Fine-tune a Resnet for custom classes

Learning objectives

At the end of the fourth workshop you will be able to:

- Explore class-activation mappings (CAM)
- Classify images with CLIP
- Clean an image dataset with Cleanlab

How are we doing this workshop

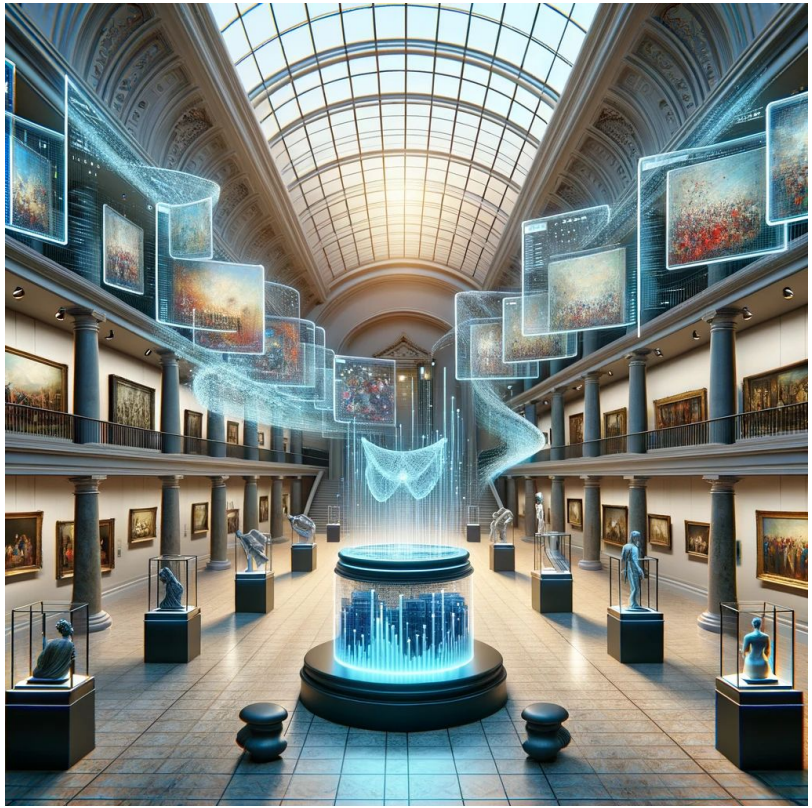
- We **type** most of the Python code from the tutorial notebooks in Google Colab

Repository:https://github.com/KISZ-BB/image-dataset-curation-workshops

What you need

- A Google user account
- A Google Drive account with enough free space
- Google Chrome or Firefox

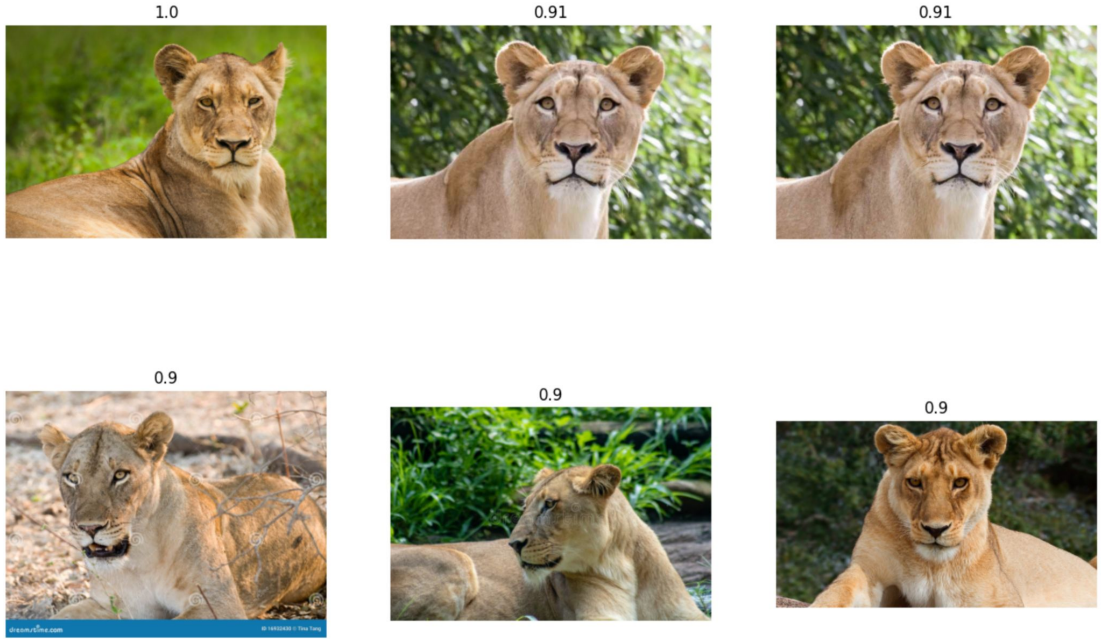
What is dataset curation?



- We want to make data **accurate** and **relevant**
- We clean, deduplicate, and label
- This is similar to what museum curators do

Quick exploration of the dataset using embeddings

Exploring the lions dataset with embeddings (Colab notebook)



Lion or not a lion?

“If you torture the data long enough, it will confess to anything” Ronald Coase, economist

- Was it a lion?

Class Activation Mapping (CAM)

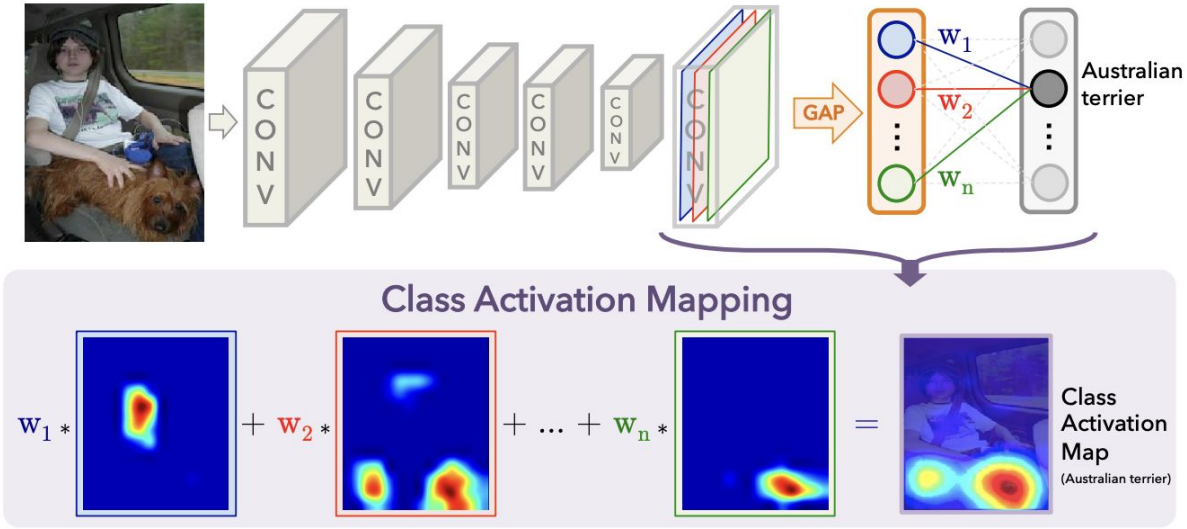
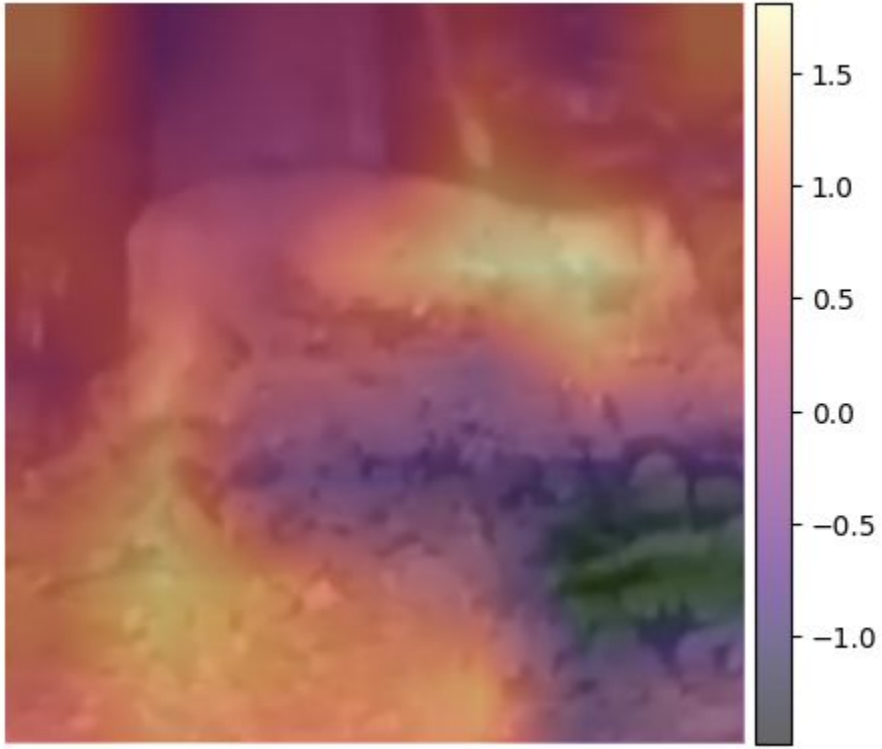


Figure 2. Class Activation Mapping: the predicted class score is mapped back to the previous convolutional layer to generate the class activation maps (CAMs). The CAM highlights the class-specific discriminative regions.

https://arxiv.org/pdf/1512.04150.pdf

Spurious correlations come from the training data

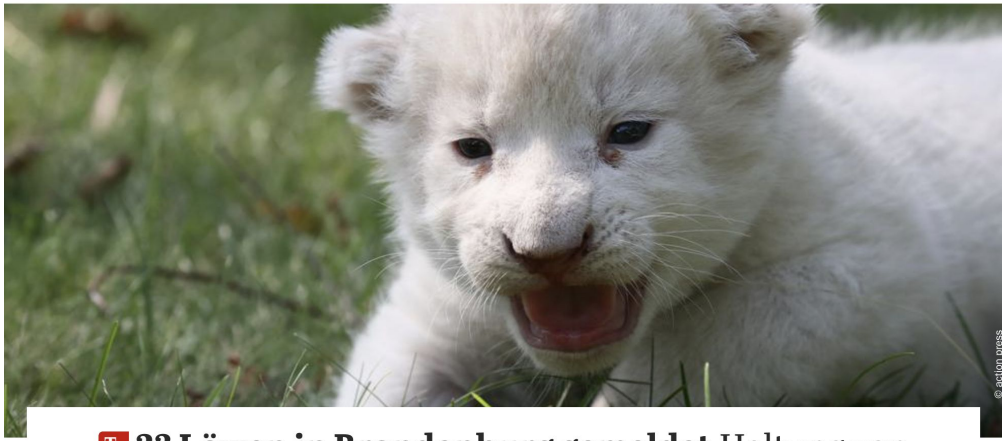


Here the model associates the **front of the animal** and the **vegetation** with the classes **'boar' (p=0.53)** and '**male lion**' **(p=0.66)**

Explore the notebook

- Which classes do you get?

- How does the CAM map look like?



T+ 23 Löwen in Brandenburg gemeldet Haltung von Großkatzen – das ist die Rechtslage in Berlin und der Region

Anders als in Brandenburg ist die private Wildtierhaltung in Berlin – mit einigen Ausnahmen – verboten. Wer es trotzdem tut, muss mit einer hohen Strafe rechnen.

Von Alexander Fröhlich und Daniel Böldt
21.07.2023, 11:43 Uhr

23 privately owned lions in Brandenburg!

OpenAI's CLIP

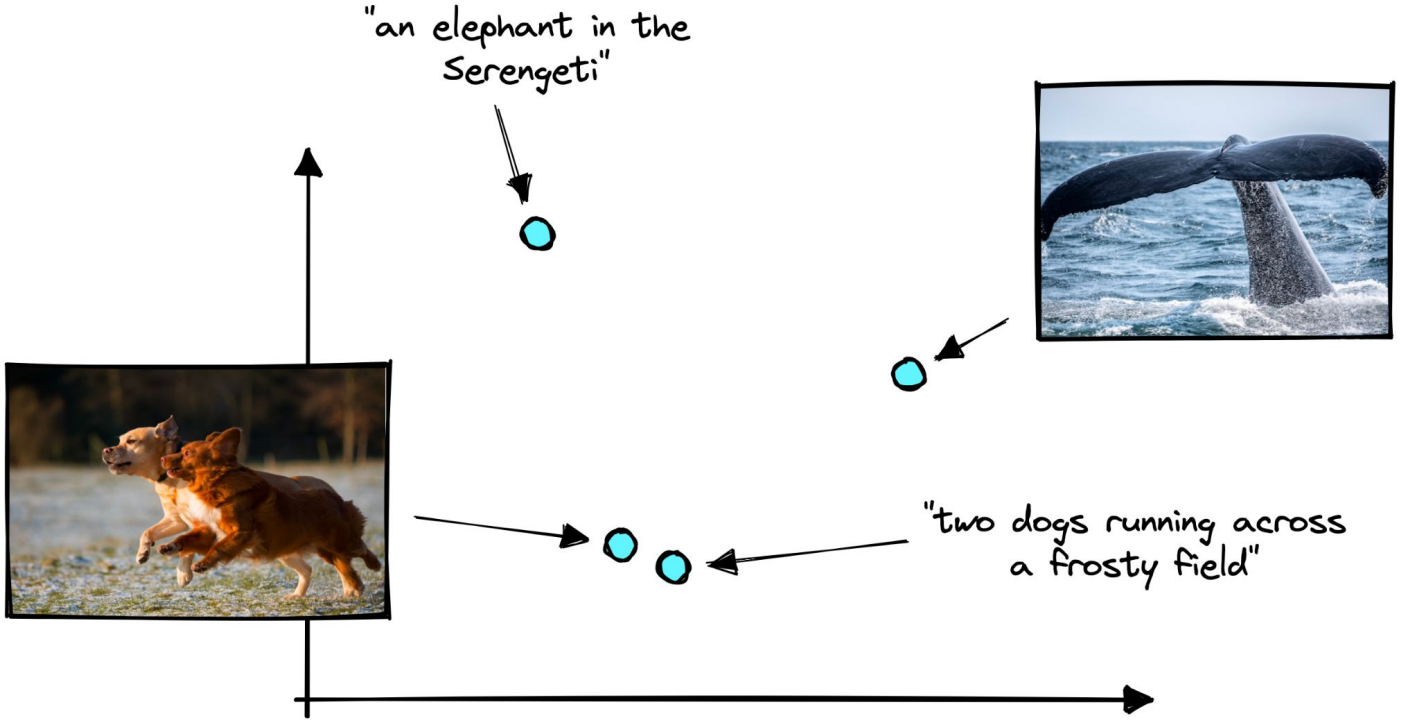
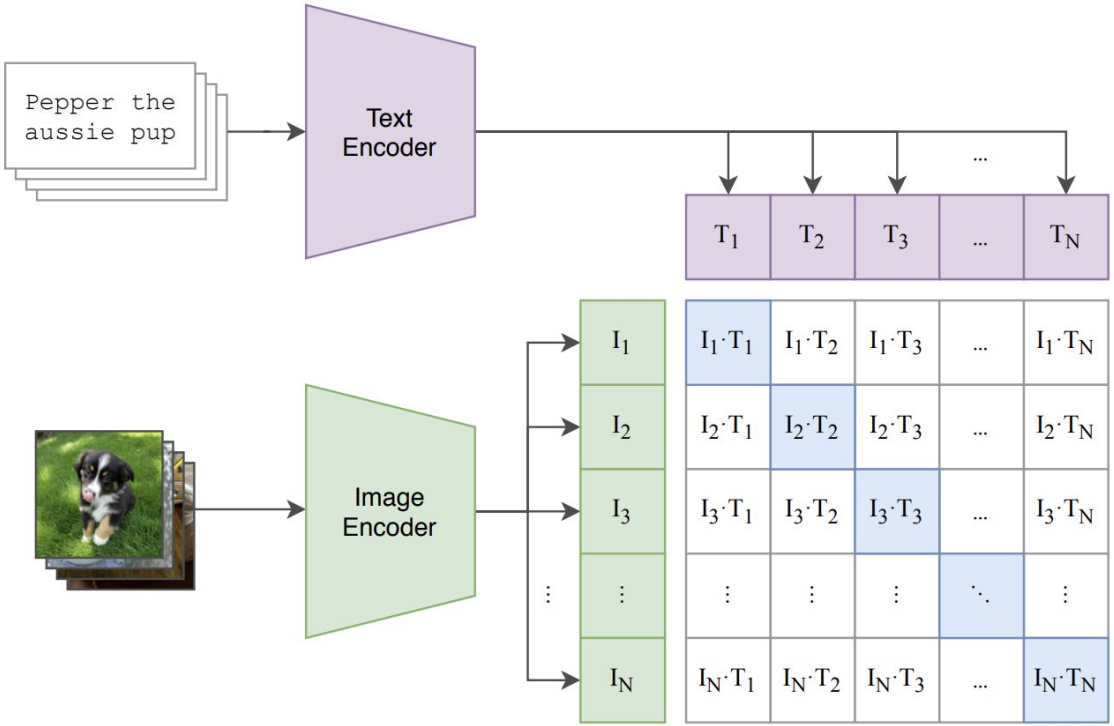


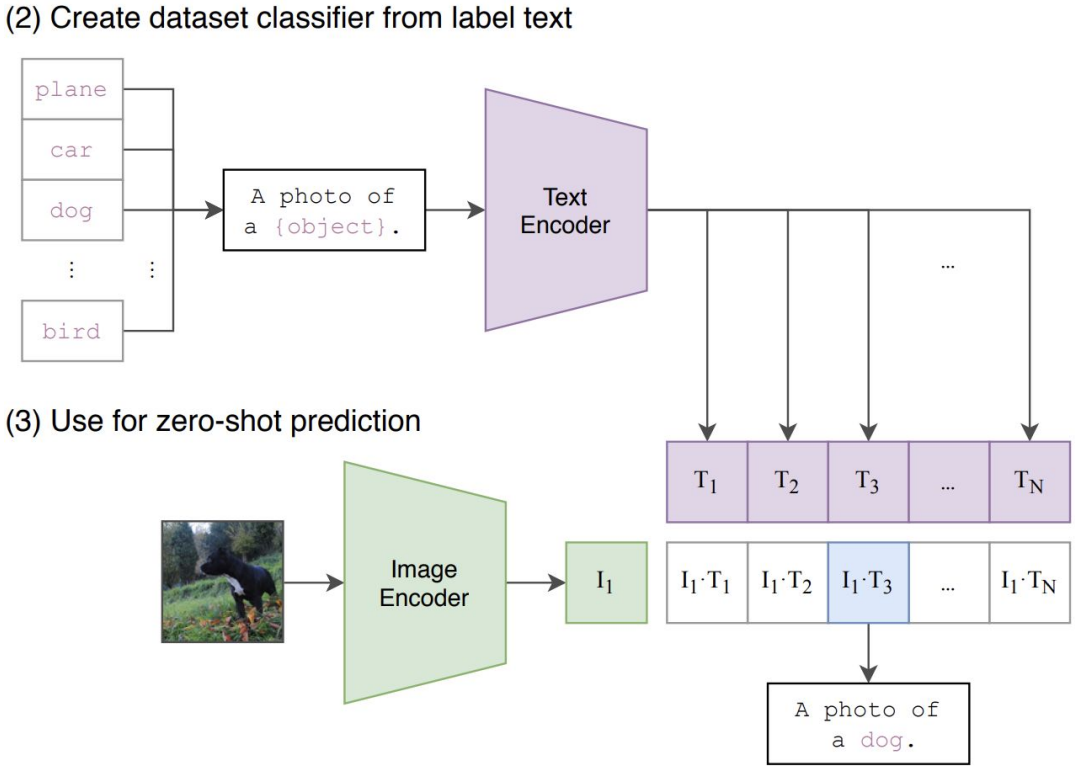
Image from pinecone's blogpost

OpenAI's CLIP

(1) Contrastive pre-training



OpenAI's CLIP



```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

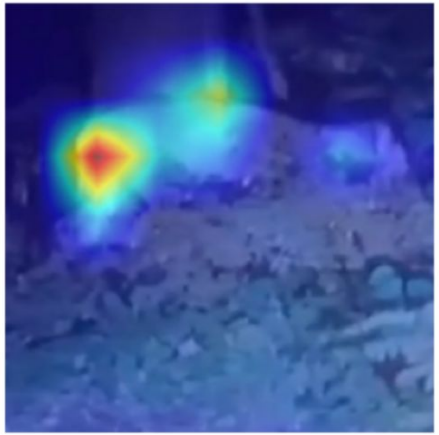
Figure 3. Numpy-like pseudocode for the core of an implementation of CLIP.

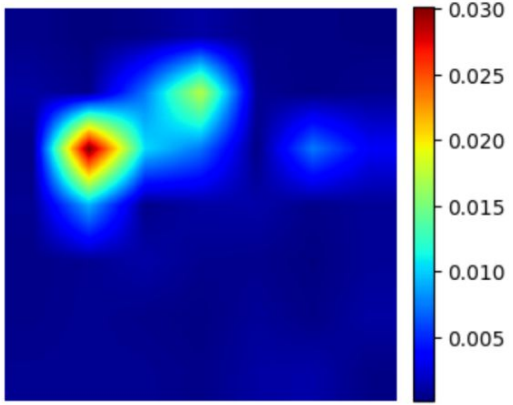
https://arxiv.org/pdf/2103.00020.pdf

CLIP Explainability

Legend: Negative Neutral Positive

True Label	Predicted Label	Attribution Label	Attribution Score	Word Importance
0	0 (0.00)	0	0.00	not a lion



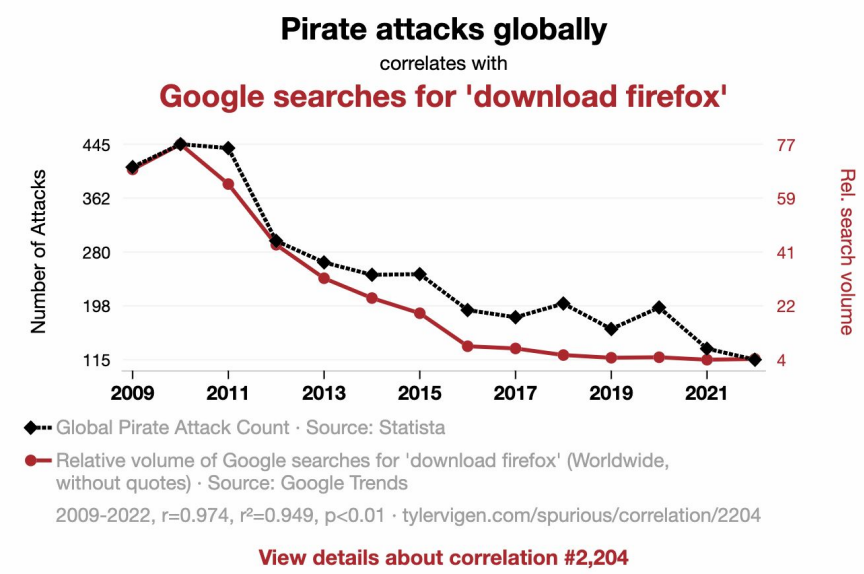


Exploring CLIP

- CLIP notebook
- CLIP explainability (requires GPU credits to run)

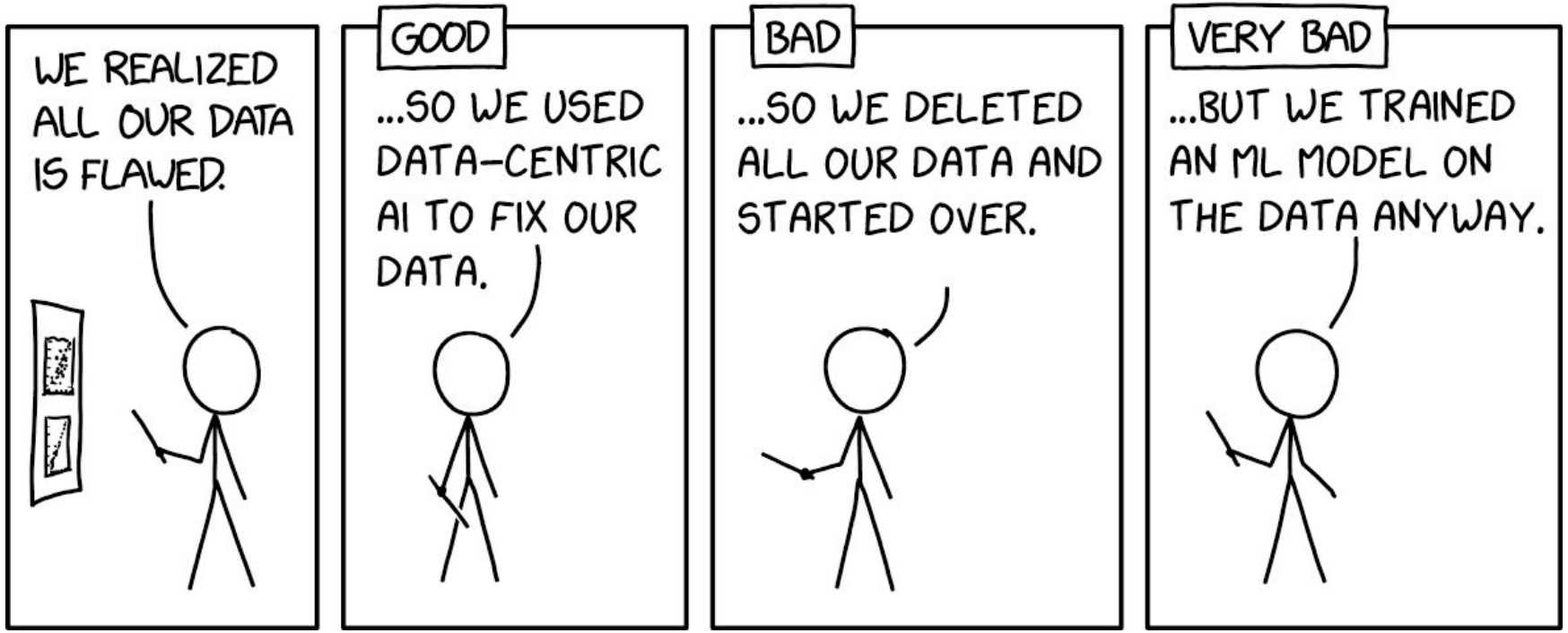
The importance of clean training data

- Improves a model's accuracy and reliability
- Reduces overfitting to spurious correlations



https://www.tylervigen.com/spurious-correlations

Data-Centric AI



MIT's Data-Centric AI Course

xkcd

Labeling errors

ImageNet given label:
tick

Cleanlab guessed: **yellow garden spider**

MTurk consensus: **yellow garden spider**

ImageNet given label:
coyote

Cleanlab guessed: **dingo**

MTurk consensus: **dingo**

ID: 00012230

https://labelerrors.com/

Cleanlab's confident learning

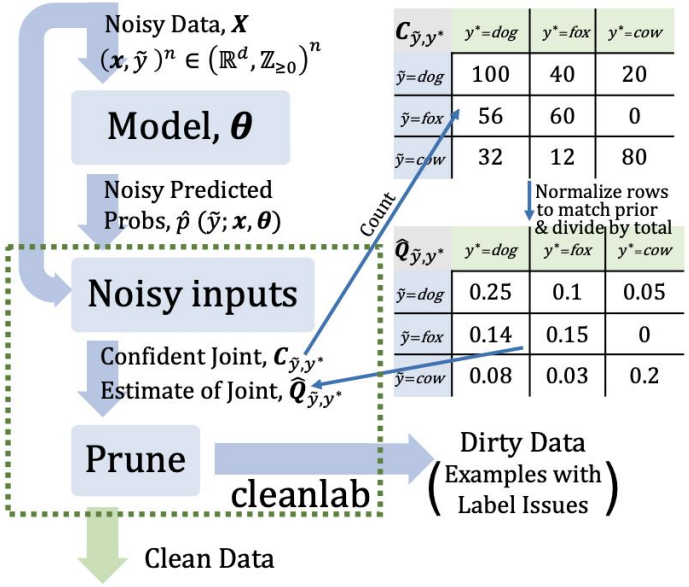


Figure 1: An example of the confident learning (CL) process. CL uses the confident joint, $\boldsymbol{C}_{\tilde{y},y^*}$, and $\hat{\boldsymbol{Q}}_{\tilde{y},y^*}$, an estimate of $\boldsymbol{Q}_{\tilde{y},y^*}$, the joint distribution of noisy observed labels $\tilde{y}$ and unknown true labels y^*, to find examples with label errors and produce clean data for training.

https://arxiv.org/pdf/1911.00068.pdf

Cleanlab and CLIP

id: 91
GL: boar
SL: cartoon

id: 37
GL: lion
SL: boar

id: 51
GL: boar
SL: cartoon

id: 76
GL: boar
SL: cartoon

id: 10
GL: lion
SL: boar

id: 17
GL: lion
SL: boar

id: 26
GL: lion
SL: boar

id: 32
GL: lion
SL: boar

id: 61
GL: boar
SL: cartoon

id: 56
GL: boar
SL: cartoon

id: 2
GL: lion
SL: boar

id: 45
GL: lion
SL: boar

id: 34
GL: lion
SL: boar

id: 40
GL: lion
SL: boar

id: 20
GL: lion
SL: boar

[Explore the Colab notebook]

Imagelab

Imagelab - a tool to identify near duplicates and low quality images

Review questions

- How does the class-activation mapping work?
- What is zero-shot classification?
- How is CLIP trained?
- Can you explain the differences between train, validation, and test sets? What are the issues of having duplicates between these sets?
- Why are the performance metrics obtained on the dirty dataset **useless**?
- Why do we need to use cross-validation to clean the dataset on cleanlab? What is hierarchical cross-validation?
- *Was it a lion?* 🤔

Join us for the next workshops!

- AI Service Center - Berlin Brandenburg

Next topics:

- **Meta’s Segment Anything**
- **Segmentation and object detection with Detectron2 and YOLOv8**
- **Using Qdrant as a vector database for images and text**
- **Deployment of a computer vision system with FastAPI and Docker**